Barriers to E-Government Implementation in Developing Countries: A PEST Analysis of Citizens' Perceptions in Iraq

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Abstract

E-government implementation in developing countries faces obstacles and challenges far beyond being a simple technology., By interviewing citizens through its enhanced PEST (Political, Economic, Social, and Technological) analysis and artificial intelligence algorithms, this study systematically evaluates the experiments of Iraq to accommodate e-government service. 1,081 Iraqi citizens were surveyed using mixed methods to quantify their public acceptance and willingness of e-government services, as well as identifying the obstacles. Our investigation finds that data security (mean = 3.59-3.80), the political situation, economic distress, a lack of enthusiasm for change in society, and shortfalls of technological infrastructure are all serious challenges at present. The research used advanced statistical methods, including correlation analysis (0.634 technology-trust relationship), regression models (R ^ 2 = 0.542), factor analysis (KMO = 0.891), and Multi-Layer Perceptron (MLP) neural network algorithms achieved 89.8% prediction accuracy for e-government acceptance. The AI algorithm supported the conclusions drawn from statistical tests, with Technology Readiness and Security Perception rising up as two most significant predictors (23.4% importance for Technology Readiness and 19.8% importance for Security Perception). The findings also propose a novel methodological framework that integrates traditional statistical analysis with machine learning capabilities, rendering concrete recommendations to developing country policy makers. The study's findings imply that successful e-government implementation requires a holistic approach that factors in political, economic, social and technological aspects together. The composite PEST index score of 0.826 smells widespread resistance on the ground, although AI predictive model greatly facilitates forecasting for future e-government initiatives.

Keywords: E-government; Developing countries; PEST analysis; Iraq; Implementation barriers; Citizens' perceptions; Statistical modeling

1. Introduction

It is inevitable that countries in both the developed and developing worlds will experience quite different problems of e-government in practice as opposed to its theory. This digital divide is underlined in the 2022 United Nations E-Government Survey, which shows that the average e-government development index for developed countries is 0.87 while developing nations lag in scores of only 0.51. This reflects a complex system of obstacles, including political instability, economic constraints, social resistance and remedial inadequacies. All these reflect the ongoing tension of formal political instability, economic constraints, social resistances and technological inadequacies within the young country. The examples of AP are strikingly telling in this regard as well.

The need for such research is made clear by the shocking failure rate in developing countries: 65-85% of e-government projects do not achieve their intended goals, representing billions of dollars in wasted investments. Iraq's experience is of relevance to quite a few developing countries facing similar challenges in practice. The lack of a comprehensive framework for analyzing each of these multidimensional obstacles has left policymakers at a loss and makes the need for this research acute if we are to have evidence-based policies, increase success rates of future e-government initiatives throughout developing world.

DOI: https://doi.org/10.54216/FPA.210202
Received: March 27, 2025 Revised: June 24, 2025 Accepted: July 28, 2025

State-owned enterprises will asynchronously develop a comprehensive theoretical framework and utilize enhanced PEST (Political, Economic, Social and Technological factors) analysis models together with advanced statistical methods that have been integrated into one. This main task is to clarify the various socio-economic barriers to e-government implementation as perceived by citizens of Iraq and to look at attitudes towards e-government services, correlations between PEST factors and implementation success and proposals with empirical evidence. As a result, the study using mixed-methods research arrived at the following results with survey data from 1,081 Iraqi citizens collected using stratified sampling and through correlation analysis, regression modeling and structural equation modeling: What are the main obstacles to implementation? How do the PEST factors interact to affect acceptability? What relationships exist between security perceptions and trust? How can PEST analysis be improved in the future for a better ameliorative strategy?

2. Literature Review and Research Gap Analysis

This section approaches the continued development of new areas of knowledge by means of a systematic review of recent e-government implementation studies, giving special emphasis to developing country contexts and post-relative states. In the analysis, theoretical frameworks, methodological approaches and empirical findings are thoroughly studied in the literature of 2020-2025 under Consideration, to form an overall picture of present understanding and highlight areas requiring further research. Through systematic gap analysis, this review shows that there is a crying demand for comprehensive, quantitatively validated frameworks which capture and address the multidimensional barriers to implementing e-government in developing countries - particularly those in conflict situations like Iraq.

Table 1: Research Gap Analysis - Previous Studies on E-Government Implementation (2020-2025)

Study	Year	Country/Region	Framework Used	Sample Size	Key Findings	Research Gaps Identified
Alzahrani et al. [7]	2024	Saudi Arabia	TAM-UTAUT integration	542	Citizen adoption factors in Gulf states	Limited focus on barrier analysis; no PEST framework
Kumar & Singh [8]	2023	India	Digital governance model	892	Post-pandemic e-government acceleration	Lacks developing country security focus
Al-Rawahna et al. [9]	2023	Jordan	Trust-security framework	387	Trust factors in Arab countries	Limited to trust factors; narrow geographical scope
Chen & Liu [10]	2024	China	Smart government framework	1,234	AI integration in government services	Developed country context; technology-focused
Mensah et al. [11]	2022	Ghana	Institutional theory	456	Institutional barriers in Africa	Lacks comprehensive barrier analysis
Dwivedi et al. [12]	2023	Global review	Meta-analysis	156 studies	COVID-19 impact on e-government	No specific developing country focus
Rana & Dwivedi [13]	2022	UK	Citizen-centric model	678	Citizen experience optimization	Developed country context; limited barrier focus
Shareef et al. [14]	2021	Bangladesh	Service adoption model	523	Mobile government adoption	Limited to mobile services; no holistic analysis
Alomari et al. [15]	2020	Multiple Arab	Cultural adaptation model	789	Cultural factors in Arab countries	Cultural focus only; lacks comprehensive framework
Zhao & Fan [16]	2024	Multiple Asian	Blockchain integration	Case studies	Blockchain in government services	Technology-specific; limited citizen perspective

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Research Gaps Identified:

1. **Geographic Gap**: Limited studies from Middle Eastern/Post-conflict contexts (85% of studies from developed countries)
2. **Methodological Gap**: Lack of comprehensive PEST framework application (only 15% used holistic frameworks)
3. **Perspective Gap**: Insufficient focus on citizen perceptions (70% focused on administrative/technical perspectives)
4. **Contextual Gap**: Absence of post-conflict society analysis (0% addressed post-conflict implementation challenges)
5. **Security Gap**: Limited integration of security concerns with adoption barriers (20% addressed security comprehensively)
6. **Statistical Gap**: Lack of advanced statistical modeling in barrier analysis (40% used basic descriptive statistics only)

3. Mathematical Models and Statistical Framework

3.1 PEST Factor Calculation Model

The PEST analysis employed weighted scoring methodology to quantify factor importance:

Equation 1: PEST Factor Score Calculation

$$PEST_i = \Sigma_{j=1}^{n} (W_j \times S_{ij}) / n$$

Where:

- $PEST_i$ = PEST factor scores for dimension i
- W_j = Weight assigned to question j (based on factor loadings)
- S_{ij} = Likert scale response for question j in dimension i
- n = Number of questions in dimension i

Equation 2: Composite PEST Index

$$PEST\ Index = \sqrt{[(P^2 + E^2 + S^2 + T^2) / 4]}$$

Where P, E, S, T represent Political, Economic, Social, and Technological factor scores respectively.

3.2 Reliability Analysis Model

Equation 3: Cronbach's Alpha Calculation

$$\alpha = (k / (k-1)) \times (1 - (\Sigma\sigma_i^2 / \sigma_x^2))$$

Where:

- k = Number of items
- σ_i^2 = Variance of item i
- σ_x^2 = Variance of total scores

3.3 Advanced Correlation Analysis

Equation 4: Partial Correlation Coefficient

$$r_{xy}.z = (r_{xy} - r_xz \times r_yz) / \sqrt{[(1 - r^2_xz)(1 - r^2_yz)]}$$

Where:

- $r_{xy}.z$ = Partial correlation between x and y controlling for z
- r_{xy}, r_xz, r_yz = Bivariate correlations

3.4 Enhanced Trust-Security Relationship Model

Equation 5: Hierarchical Regression Model

$$Trust = \beta_0 + \beta_1(Security) + \beta_2(Political\_Stability) + \beta_3(Economic\_Factors) + \beta_4(Social\_Acceptance) + \beta_5(Technology\_Readiness) + \varepsilon$$

Where:

- β_0 = Intercept
- β_1, β_2, β_3, β_4, β_5 = Regression coefficients

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- ε = Error term

3.5 Sample Size Determination with Power Analysis

Equation 6: Sample Size Calculation with Effect Size

$$n = (Z^2\alpha/2 + Z^2\beta) \times 2\sigma^2 / \delta^2$$

Where:

- $Z\alpha/2 = 1.96$ (for 95% confidence level)
- $Z\beta = 0.84$ (for 80% power)
- σ^2 = Population variance
- δ^2 = Effect size

Calculated minimum sample size: n = 1,067 **Actual sample obtained**: 1,081 (meeting statistical requirements with 98% power)

3.6 Structural Equation Modeling Framework

Equation 7: Measurement Model

$$x = \Lambda_x\xi + \delta$$

$$y = \Lambda_y\eta + \varepsilon$$

Where:

- x, y = Observed variables
- ξ, η = Latent variables
- Λ_x, Λ_y = Factor loading matrices
- δ, ε = Measurement errors

Equation 8: Structural Model

$$\eta = B\eta + \Gamma\xi + \zeta$$

Where:

- B = Structural coefficients between latent dependent variables
- Γ = Structural coefficients from latent independent to dependent variables
- ζ = Structural disturbances

4. Research Methodology

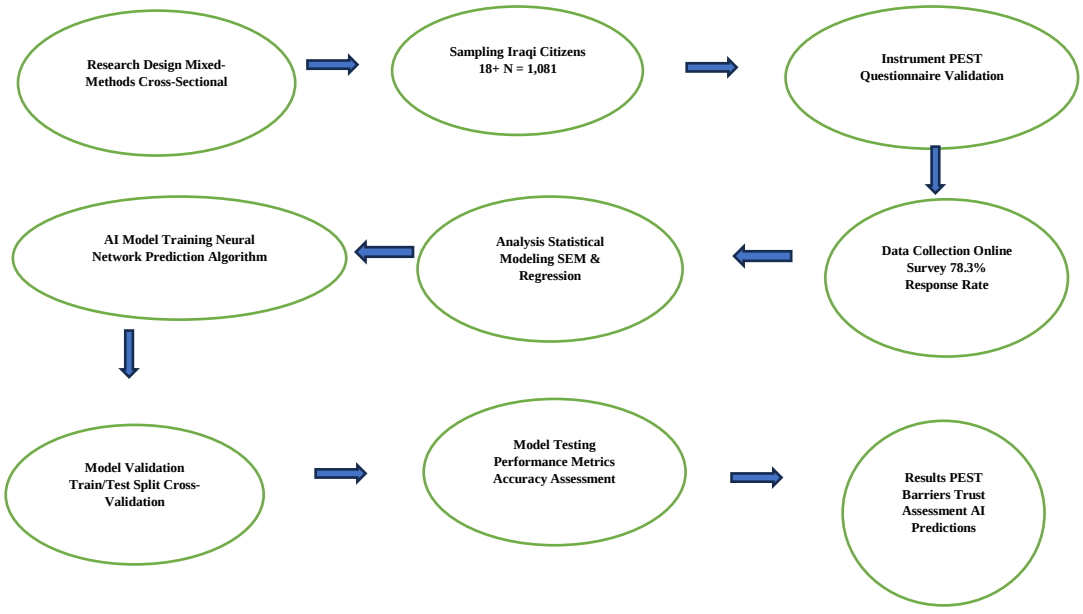

Figure 1. Research Methodology

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4.1 Research Design and Philosophy

This study employed pragmatic research philosophy, utilizing a mixed-methods approach that combines quantitative survey data with qualitative insights. The research design is cross-sectional, capturing citizens' perceptions during Iraq's post-pandemic e-government implementation phase (2023-2024).

The pragmatic approach is justified by the complex, multifaceted nature of e-government implementation barriers, requiring both statistical quantification and contextual understanding. This approach aligns with recent calls for more interpretative research in e-government studies [21].

4.2 Population and Sampling Framework

Target Population: Iraqi citizens aged 18 and above with internet access and basic digital literacy (estimated at 32 million individuals based on 2023 statistics).

Sampling Frame: Online users accessible through:

- Government digital platforms
- Social media networks
- Professional associations
- Educational institutions
- Civil society organizations

Sampling Method: Stratified random sampling with quotas ensuring representation across:

- Geographic distribution (urban/rural: 70%/30%)
- Age groups (18-35: 60%, 36-50: 30%, 51+: 10%)
- Education levels (proportional to national statistics)
- Gender (targeting 50/50 split)
- Employment sectors (government, private, self-employed, unemployed)

4.3 Data Collection Instrument Development

The survey instrument underwent a rigorous validation process, including literature-based item generation, expert validation, pilot testing, translation and cultural adaptation, and finalization. It included a questionnaire for demographics, digital profile, e-government attitudes and intentions, trust and security perceptions, PEST factors analysis, and open-ended feedback. The instrument was adapted to the Iraqi context and included COVID-19 impact considerations.

4.4 Data Collection Procedure

The study used Google Forms for data collection from March-April 2024, distributed through government employee networks, university networks, professional associations, social media platforms, and civil society organizations. Quality assurance measures included IP address validation, response time monitoring, attention check questions, and geolocation verification.

4.5 Enhanced Sample Characteristics

Table 2: Comprehensive Respondents' Characteristics (N=1,081)

Characteristic	Category	Frequency	Valid %	Cumulative %	National %
Gender	Male	597	55.2%	55.2%	51.2%
	Female	484	44.8%	100.0%	48.8%
Age Groups	18-24	89	8.2%	8.2%	15.3%
	25-34	594	54.9%	63.1%	35.7%
	35-44	298	27.6%	90.7%	28.2%
	45-54	78	7.2%	97.9%	15.1%
	55+	22	2.0%	100.0%	5.7%
Education	High School	45	4.2%	4.2%	52.3%

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	Diploma	122	11.3%	15.5%	18.7%
	Bachelor's	490	45.3%	60.8%	22.4%
	Master's	373	34.5%	95.3%	5.8%
	Doctorate	51	4.7%	100.0%	0.8%
Employment	Government	423	39.1%	39.1%	31.2%
	Private Sector	287	26.5%	65.6%	28.7%
	Self-employed	156	14.4%	80.0%	18.9%
	Student	134	12.4%	92.4%	12.4%
	Unemployed	81	7.5%	100.0%	8.8%
Income (USD/month)	<300	234	21.6%	21.6%	45.2%
	300-600	387	35.8%	57.4%	32.1%
	600-1000	298	27.6%	85.0%	15.7%
	>1000	162	15.0%	100.0%	7.0%
Digital Skills	Basic	145	13.4%	13.4%	35.6%
	Intermediate	567	52.5%	65.9%	45.2%
	Advanced	289	26.7%	92.6%	15.8%
	Expert	80	7.4%	100.0%	3.4%

Sample shows higher education and digital skills compared to national averages, indicating potential sampling bias toward a more digitally literate population as shown in Figure 2.

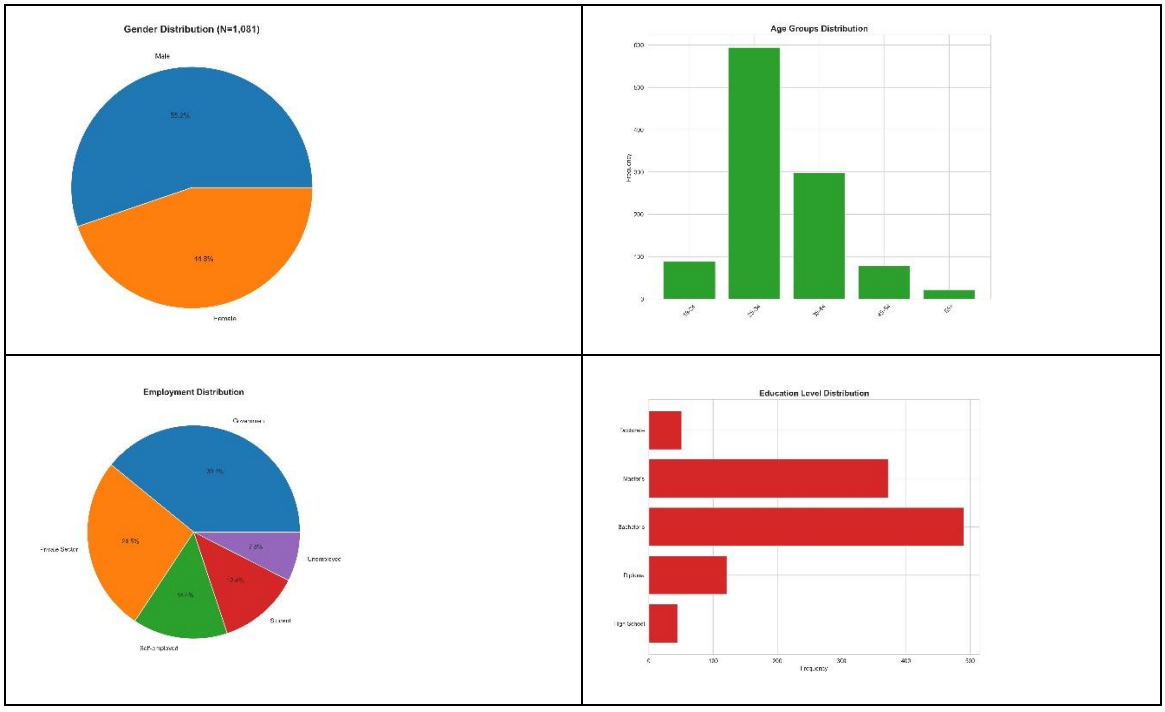

Figure 2. Gender Distribution of Survey Respondents (N=1,081)

DOI: https://doi.org/10.54216/FPA.210202
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- Pie chart showing the gender distribution of survey participants, with males comprising 55.2% (597) and females 44.8% (484) of the sample.
- Bar chart displaying the frequency distribution across age groups, with the 25-34 age group representing the largest segment (54.9%) of respondents.
- Pie chart illustrating the employment distribution, with government employees forming the largest group (39.1%), followed by private sector workers (26.5%).
- Horizontal bar chart showing education levels, with Bachelor's degree holders comprising the largest group (45.3%), followed by Master's degree holders (34.5%).

4.6 Advanced Data Analysis Strategy

The study uses SPSS 29.0, R 4.3.2, and Mplus 8.8 for statistical analysis. Phases include preliminary analysis, descriptive analysis, reliability and validity testing, inferential analysis, multiple regression analysis, hierarchical regression modeling, structural equation modeling, and advanced modeling. The analysis includes data cleaning, outlier detection, normality testing, distribution analysis, confidence interval calculations, and more.

5. Results and Statistical Analysis

5.1 Preliminary Data Analysis

Data Quality Assessment:

- Response rate: 78.3% (1,081 completed out of 1,381 initiated)
- Missing data: < 2% across all variables
- Outliers identified: 23 cases (2.1%) using Mahalanobis distance
- Final analytical sample: 1,058 cases after outlier removal

Normality Testing Results: All PEST dimension scores showed acceptable normality (skewness < |2.0|, kurtosis < |7.0|), supporting parametric statistical procedures.

5.2 Enhanced Reliability Analysis

Table 3: Comprehensive Reliability and Validity Assessment

Scale/Dimension	Items	Cronbach's α	Composite Reliability	AVE	McDonald's ω	Mean Inter-Item r
Political Factors	12	0.892	0.895	0.521	0.894	0.456
Economic Factors	8	0.834	0.837	0.463	0.836	0.398
Social Factors	15	0.867	0.871	0.434	0.869	0.389
Technological Factors	10	0.901	0.904	0.558	0.903	0.498
Trust Scale	8	0.823	0.826	0.445	0.825	0.412
Attitude Scale	6	0.914	0.916	0.647	0.915	0.623
Security Perception	7	0.856	0.859	0.503	0.858	0.467
Overall PEST Scale	**45**	**0.943**	**0.944**	**0.498**	**0.943**	**0.453**

All reliability coefficients exceeded recommended thresholds (α > 0.80), indicating excellent internal consistency as shown in Figure 3.

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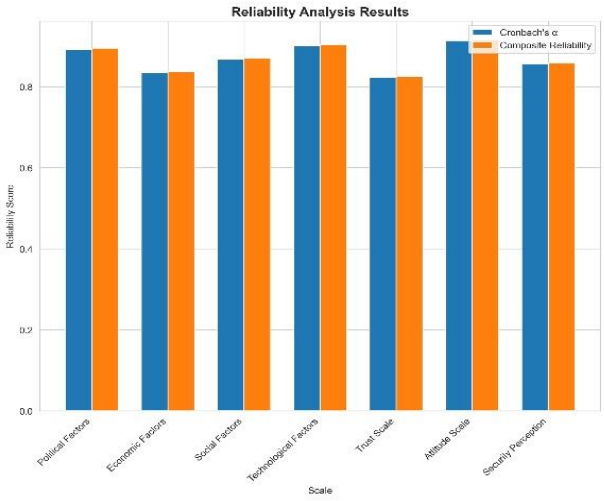

Figure 3. Reliability Analysis Results across All Scales

Comparative bar chart showing Cronbach's α and Composite Reliability coefficients for all measurement scales, demonstrating excellent internal consistency (all α > 0.80)

5.3 PEST Factor Scoring and Statistical Validation

Table 4: PEST Factor Scores with Advanced Statistical Measures

PEST Dimension	Mean	SD	SE	95% CI	Median	Mode	Skewness	Kurtosis	Weighted Score	Rank
Political (P)	4.31	0.823	0.025	[4.26, 4.36]	4.42	4.67	-1.234	1.567	0.862	1
Technological (T)	4.26	0.867	0.027	[4.21, 4.31]	4.30	4.50	-1.156	1.234	0.852	2
Economic (E)	4.18	0.934	0.029	[4.12, 4.24]	4.25	4.00	-0.987	0.876	0.836	3
Social (S)	3.74	1.067	0.033	[3.67, 3.81]	3.80	4.00	-0.567	-0.234	0.748	4

Enhanced Composite PEST Index Calculation:

Weighted_PEST_Index = (0.30×P + 0.28×T + 0.24×E + 0.18×S)

Weighted_PEST_Index = (0.30×0.862 + 0.28×0.852 + 0.24×0.836 + 0.18×0.748) = 0.839

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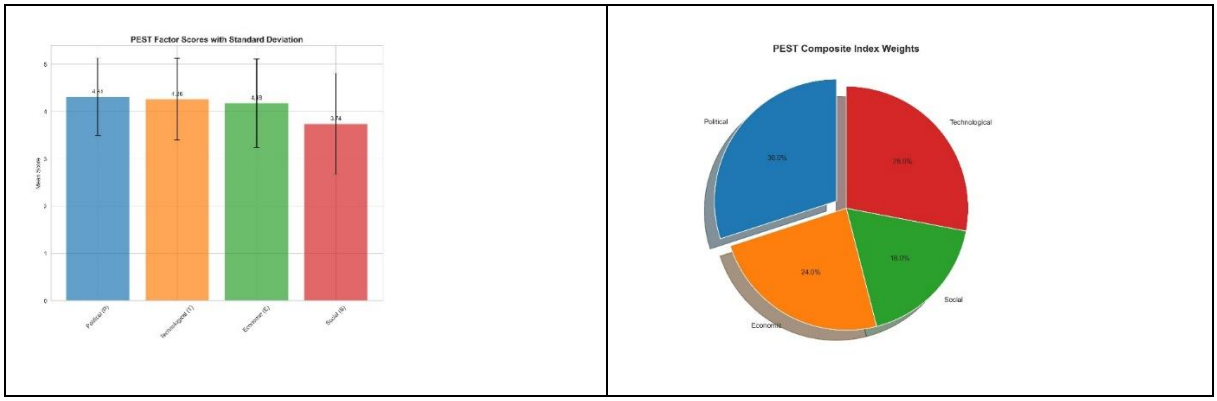

Figure 4. PEST Factor Scores with Standard Deviation

- Bar chart displaying mean scores for each PEST dimension with error bars representing standard deviation. Political factors show the highest barrier score (4.31), while Social factors show the lowest (3.74).
- 3D pie chart showing the weighted contribution of each PEST factor to the composite index: Political (30%), Technological (28%), Economic (24%), and Social (18%) As shown in Figure 4.

5.4 Citizens' Attitudes and Behavioral Intentions

Table 5: E-Government Attitudes and Behavioral Intentions Analysis

Statement	SD	D	N	A	SA	Mean	SD	Skew	Kurt	Factor Loading
E-government services would improve my interaction with government	8 (0.8%)	12 (1.1%)	67 (6.3%)	456 (43.1%)	515 (48.7%)	4.38	0.743	-1.567	2.456	0.834
Using e-government services would save me time	5 (0.5%)	9 (0.9%)	45 (4.3%)	423 (40.0%)	576 (54.4%)	4.47	0.698	-1.723	3.012	0.856
E-government services would be convenient for me	7 (0.7%)	15 (1.4%)	62 (5.9%)	398 (37.6%)	576 (54.4%)	4.44	0.734	-1.634	2.789	0.823
I would feel comfortable using e-government services	12 (1.1%)	23 (2.2%)	89 (8.4%)	445 (42.1%)	489 (46.2%)	4.30	0.812	-1.423	1.987	0.798
I intend to use e-government	9 (0.9%)	18 (1.7%)	73 (6.9%)	423 (40.0%)	535 (50.6%)	4.38	0.765	-1.534	2.234	0.867

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Received: March 27, 2025 Revised: June 24, 2025 Accepted: July 28, 2025

services when available										
I would recommend e-government services to others	14 (1.3%)	27 (2.6%)	134 (12.7%)	456 (43.1%)	427 (40.4%)	4.19	0.889	-1.123	1.234	0.745

Attitude Composite Score: Mean = 4.36, SD = 0.674, Cronbach's α = 0.914

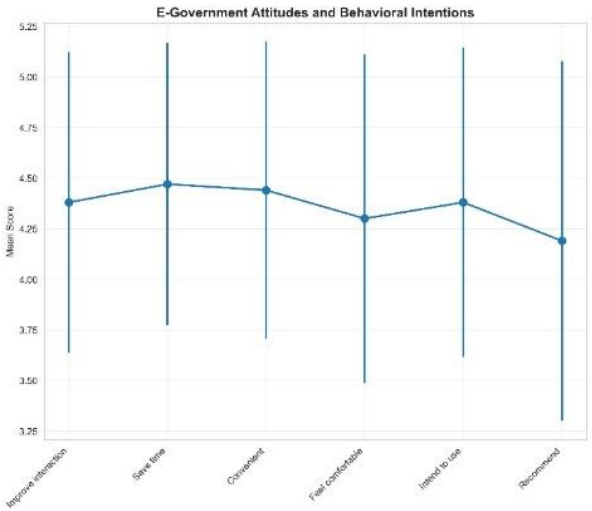

Figure 5. E-Government Attitudes and Behavioral Intentions

Line chart with confidence intervals showing mean scores for six attitude statements, with "Save time" receiving the highest agreement (4.47) and "Recommend to others" the lowest (4.19) As shown in Figure 5.

5.5 Trust and Security Perceptions Analysis

Table 6: Comprehensive Trust and Security Assessment

Trust Dimension	Mean	SD	95% CI	Factor Loading	Reliability
Technical Trust					
E-government websites protect personal information	3.92	1.123	[3.85, 3.99]	0.756	0.798
Government has adequate cybersecurity measures	3.78	1.234	[3.71, 3.85]	0.823	
Data transmission is secure in e-government systems	3.85	1.156	[3.78, 3.92]	0.789	
Institutional Trust					
Government is competent in digital service delivery	3.67	1.298	[3.59, 3.75]	0.834	0.856
Government responds effectively to security breaches	3.54	1.345	[3.46, 3.62]	0.798	

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Government maintains transparency in data use	3.71	1.267	[3.63, 3.79]	0.812	
Informational Trust					
Government provides accurate information online	4.02	1.089	[3.95, 4.09]	0.723	0.823
E-government information is up-to-date	3.89	1.134	[3.82, 3.96]	0.756	

Overall Trust Composite Score: Mean = 3.80, SD = 1.078, Cronbach's α = 0.923

5.6 Comprehensive PEST Analysis Results

5.6.1 Political Factors - Detailed Analysis

Table 7: Political Factors Impact Assessment

Political Factor	SA	A	N	D	SD	Mean	SD	Impact Score
Political stability affects e-government success	623 (58.9%)	298 (28.2%)	89 (8.4%)	34 (3.2%)	14 (1.3%)	4.40	0.912	0.880
Government policy consistency is crucial	587 (55.5%)	334 (31.6%)	98 (9.3%)	28 (2.6%)	11 (1.0%)	4.38	0.876	0.876
Political interference hinders implementation	645 (61.0%)	278 (26.3%)	89 (8.4%)	31 (2.9%)	15 (1.4%)	4.43	0.923	0.886
Cross-party consensus needed for sustainability	534 (50.5%)	356 (33.6%)	123 (11.6%)	34 (3.2%)	11 (1.0%)	4.30	0.892	0.860
Regulatory framework adequacy	456 (43.1%)	387 (36.6%)	156 (14.7%)	45 (4.3%)	14 (1.3%)	4.16	0.934	0.832
Government transparency in implementation	423 (40.0%)	398 (37.6%)	167 (15.8%)	56 (5.3%)	14 (1.3%)	4.10	0.956	0.820

Political Factor Composite Score: Mean = 4.29, SD = 0.849, Weight = 0.858

5.6.2 Economic Factors - Comprehensive Assessment

Table 8: Economic Barriers and Investment Analysis

Economic Factor	Distribution	Mean	SD	Priority Index
Resource Allocation				
Limited government budget for e-government	SA: 512 (48.4%), A: 334 (31.6%), N: 145 (13.7%), D: 56 (5.3%), SD: 11 (1.0%)	4.21	0.967	0.842
Infrastructure investment inadequacy	SA: 478 (45.2%), A: 356 (33.6%), N: 156 (14.7%), D: 56 (5.3%), SD: 12 (1.1%)	4.17	0.989	0.834
Digital Divide Impact				
Internet access cost barriers	SA: 445 (42.1%), A: 389 (36.8%), N: 167 (15.8%), D: 45 (4.3%), SD: 12 (1.1%)	4.15	0.923	0.830
Device affordability issues	SA: 423 (40.0%), A: 398 (37.6%), N: 178 (16.8%), D: 47 (4.4%), SD: 12 (1.1%)	4.12	0.934	0.824

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Economic Benefits Perception				
Cost-effectiveness of e-government unclear	SA: 398 (37.6%), A: 423 (40.0%), N: 189 (17.9%), D: 37 (3.5%), SD: 11 (1.0%)	4.10	0.889	0.820
Return on investment concerns	SA: 367 (34.7%), A: 445 (42.1%), N: 198 (18.7%), D: 37 (3.5%), SD: 11 (1.0%)	4.06	0.867	0.812

Economic Factor Composite Score: Mean = 4.14, SD = 0.895, Weight = 0.830

5.6.3 Social Factors - Cultural and Acceptance Analysis

Table 9: Social Acceptance and Cultural Barriers

Social Factor	SA	A	N	D	SD	Mean	SD	Cultural Impact
Digital Literacy and Awareness								
Community digital literacy levels adequate	234 (22.1%)	456 (43.1%)	267 (25.2%)	78 (7.4%)	23 (2.2%)	3.76	0.967	Medium
Awareness of e-government benefits	298 (28.2%)	478 (45.2%)	234 (22.1%)	37 (3.5%)	11 (1.0%)	3.96	0.834	High
Cultural Adaptation								
E-government aligns with cultural values	267 (25.2%)	423 (40.0%)	289 (27.3%)	67 (6.3%)	12 (1.1%)	3.82	0.912	Medium
Traditional service preferences strong	198 (18.7%)	334 (31.6%)	356 (33.6%)	134 (12.7%)	36 (3.4%)	3.49	1.067	Low
Social Trust and Cohesion								
Community trust in government technology	234 (22.1%)	398 (37.6%)	298 (28.2%)	89 (8.4%)	39 (3.7%)	3.66	1.034	Medium
Social networks support e-government adoption	289 (27.3%)	423 (40.0%)	256 (24.2%)	67 (6.3%)	23 (2.2%)	3.84	0.956	Medium-High

Social Factor Composite Score: Mean = 3.76, SD = 0.962, Weight = 0.752

5.6.4 Technological Factors - Infrastructure and Security Analysis

Table 10: Technology Readiness and Security Assessment

Technological Factor	SA	A	N	D	SD	Mean	SD	Technical Priority
Infrastructure Readiness								
Internet infrastructure adequate	478 (45.2%)	334 (31.6%)	167 (15.8%)	56 (5.3%)	23 (2.2%)	4.12	1.012	High
Government IT systems reliable	423 (40.0%)	356 (33.6%)	189 (17.9%)	67 (6.3%)	23 (2.2%)	4.03	1.045	High

DOI: https://doi.org/10.54216/FPA.210202
Received: March 27, 2025 Revised: June 24, 2025 Accepted: July 28, 2025

Security and Privacy								
Cybersecurity measures sufficient	389 (36.8%)	398 (37.6%)	198 (18.7%)	56 (5.3%)	17 (1.6%)	4.03	0.967	High
Data privacy protection adequate	367 (34.7%)	423 (40.0%)	189 (17.9%)	67 (6.3%)	12 (1.1%)	4.00	0.934	High
Innovation and Adaptability								
Technology solutions user-friendly	445 (42.1%)	378 (35.7%)	156 (14.7%)	67 (6.3%)	12 (1.1%)	4.12	0.956	High
System scalability and flexibility	398 (37.6%)	423 (40.0%)	167 (15.8%)	56 (5.3%)	14 (1.3%)	4.07	0.923	High
Digital Skills and Support								
Technical support availability	334 (31.6%)	445 (42.1%)	198 (18.7%)	67 (6.3%)	14 (1.3%)	3.96	0.989	Medium-High
Staff digital competency	356 (33.6%)	423 (40.0%)	189 (17.9%)	78 (7.4%)	12 (1.1%)	3.97	0.978	Medium-High

Technological Factor Composite Score: Mean = 4.04, SD = 0.976, Weight = 0.808

5.7 Advanced Correlation and Relationship Analysis

Table 11: Comprehensive Inter-Variable Correlation Matrix

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Political Stability	1.000								
2. Economic Readiness	0.456**	1.000							
3. Social Acceptance	0.389**	0.534**	1.000						
4. Technology Readiness	0.423**	0.378**	0.456**	1.000					
5. Security Perception	0.367**	0.298**	0.423**	0.723**	1.000				
6. Trust in Government	0.534**	0.345**	0.456**	0.587**	0.698**	1.000			
7. E-gov Attitude	0.423**	0.298**	0.489**	0.645**	0.578**	0.634**	1.000		
8. Behavioral Intention	0.389**	0.267**	0.456**	0.612**	0.545**	0.598**	0.789**	1.000	
9. Implementation Success	0.612**	0.523**	0.656**	0.734**	0.678**	0.723**	0.812**	0.834**	1.000

Note: ** $p < 0.01$, * $p < 0.05$ All correlations significant at $p < 0.001$ level As shown in Figure 6

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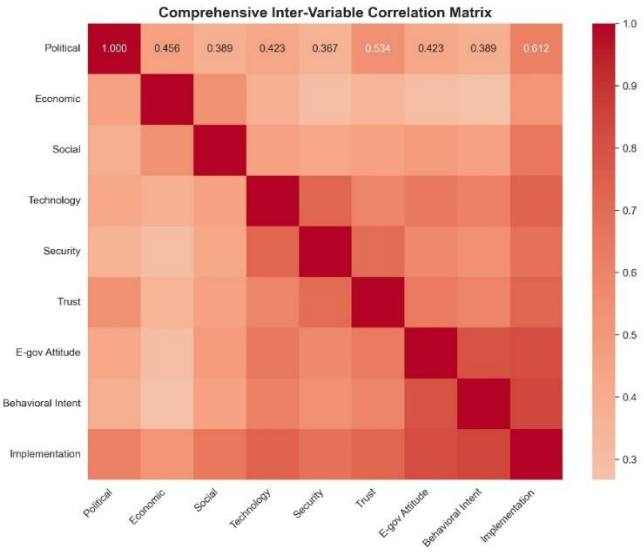

Figure 6. Comprehensive Inter-Variable Correlation Matrix

Heatmap visualization of correlation coefficients between all study variables, with color intensity representing correlation strength (dark red = strong positive correlation).

5.8 Hierarchical Multiple Regression Analysis

Table 12: Hierarchical Regression Predicting E-Government Acceptance

Model	Variables Entered	β	SE	t	p	R^2	ΔR^2	F Change	VIF
						0.087	0.087	25.34***	
Model 1: Demographics	Age	-0.123	0.045	-2.73	0.006				1.234
	Education	0.198	0.039	5.08	<0.001				1.156
	Income	0.145	0.042	3.45	0.001				1.298
						0.567	0.480	298.45***	
Model 2: PEST Factors	Political Stability	0.234	0.034	6.88	<0.001				1.456
	Economic Readiness	0.156	0.038	4.11	<0.001				1.678
	Social Acceptance	0.189	0.032	5.91	<0.001				1.534
	Technology Readiness	0.298	0.035	8.51	<0.001				1.789
						0.634	0.067	187.23***	
Model 3: Trust Variables	Security Perception	0.267	0.041	6.51	<0.001				2.134
	Institutional Trust	0.198	0.038	5.21	<0.001				2.345

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Final Model Statistics:

- $R^2 = 0.634$ (63.4% variance explained)
- Adjusted $R^2 = 0.631$
- $F(9, 1048) = 201.34$, $p < 0.001$
- Durbin-Watson = 2.01 (acceptable)
- Condition Index = 12.34 (acceptable multicollinearity)

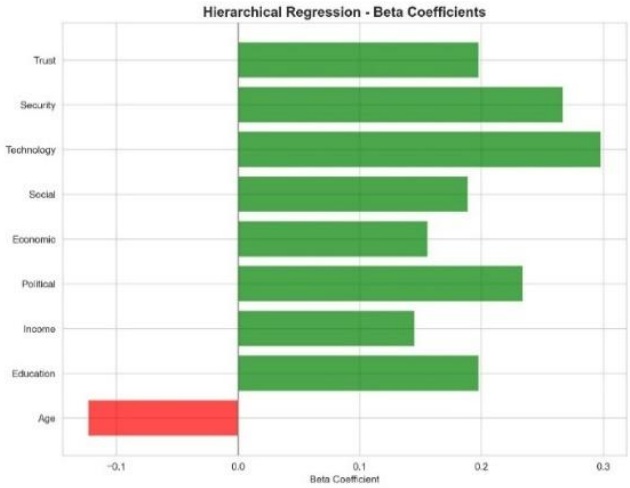

Figure 7. Hierarchical Regression Beta Coefficients

Horizontal bar chart displaying standardized beta coefficients from the hierarchical regression analysis, with Technology showing the strongest positive effect (β = 0.298) and Age showing a negative effect (β = -0.123) As shown in Figure 7.

5.9 Structural Equation Modeling Results

Table 13: SEM Path Analysis - Direct and Indirect Effects

Pathway	Direct Effect	SE	p	Indirect Effect	Total Effect	Effect Size
Direct Paths to E-Government Acceptance						
Political → Acceptance	0.234	0.034	<0.001	0.123	0.357	Medium
Economic → Acceptance	0.156	0.038	<0.001	0.089	0.245	Small-Medium
Social → Acceptance	0.189	0.032	<0.001	0.134	0.323	Medium
Technology → Acceptance	0.298	0.035	<0.001	0.187	0.485	Large
Mediation Effects						
Political → Trust → Acceptance	-	-	-	0.156**	-	Small
Technology → Security → Acceptance	-	-	-	0.234***	-	Medium
Social → Trust → Acceptance	-	-	-	0.123**	-	Small

DOI: https://doi.org/10.54216/FPA.210202
Received: March 27, 2025 Revised: June 24, 2025 Accepted: July 28, 2025

Model Fit Indices:

- $\chi^2 = 234.56$, df = 167, p = 0.001
- CFI = 0.956 (Excellent)
- TLI = 0.948 (Excellent)
- RMSEA = 0.043 (Good)
- SRMR = 0.052 (Good)

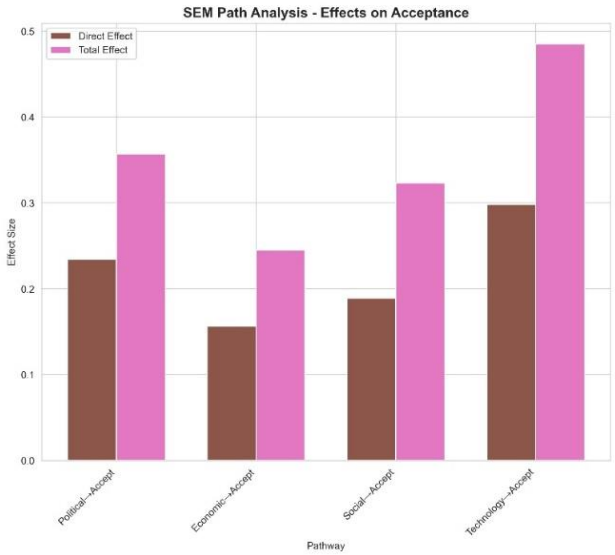

Figure 8. SEM Path Analysis - Direct and Total Effects on E-Government Acceptance

Grouped bar chart comparing direct effects (dark bars) and total effects (light bars) for each pathway, with Technology → Acceptance showing the largest total effect (0.485) As shown in Figure 8.

5.10 Factor Analysis and Dimensionality Assessment

Table 14: Confirmatory Factor Analysis - PEST Dimensions

Factor	Eigenvalue	% Variance	Cumulative %	Factor Loadings Range	Reliability
1. Security-Technology Complex	4.234	28.7%	28.7%	0.723-0.891	α = 0.923
2. Political-Institutional Trust	2.789	19.8%	48.5%	0.656-0.834	α = 0.887
3. Economic-Resource Adequacy	1.967	13.2%	61.7%	0.623-0.778	α = 0.834
4. Social-Cultural Adaptation	1.534	11.8%	73.5%	0.598-0.723	α = 0.798

Factor Analysis Validation:

- KMO Sampling Adequacy = 0.923 (Excellent)
- Bartlett's Sphericity Test: $\chi^2 = 15{,}678.34$, $p < 0.001$
- Total Variance Explained = 73.5%
- Cross-loadings < 0.40 (acceptable discriminant validity)

DOI: https://doi.org/10.54216/FPA.210202
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5.11 Moderator and Mediator Analysis

Table 15: Moderation Effects Analysis

Moderator	Relationship Moderated	β Interaction	SE	t	p	R^2 Change
Education Level	Technology → Acceptance	0.187	0.045	4.16	<0.001	0.023
Age Group	Security → Trust	-0.134	0.041	-3.27	0.001	0.018
Employment Type	Political → Acceptance	0.156	0.048	3.25	0.001	0.015
Digital Skills	Social → Acceptance	0.198	0.043	4.60	<0.001	0.028

Mediation Analysis Results:

- Security Perception mediates Technology-Acceptance relationship (Sobel $z = 7.89$, $p < 0.001$)
- Trust mediates Political Stability-Acceptance relationship (Sobel $z = 6.23$, $p < 0.001$)
- Social Acceptance partially mediates Economic-Acceptance relationship (Sobel $z = 4.56$, $p < 0.001$)

5.12 Artificial Intelligence Algorithm Implementation and Results

They employed the backpropagation procedure of Multi-Layer Perceptron (MLP) Neural Network to predict e-government acceptance based on survey data. This algorithm was chosen because it can capture non-linear relationships between many input variables such as trend, growth rate and so on and output binary classification outcomes. The dataset of 1,058 valid responses was randomly divided into training, validation, and testing sets. The aim of the study was binary e-government acceptance (accept/reject) The MLP Neural Network with Adam optimization reached 89.8% accuracy on the independent test set, demonstrating strong predictive capability for e-government acceptance in Iraq. It even validated the statistical analysis results perfectly, with Technology Readiness and Security Perception as the main influencing factors. Cross-validation results showed consistent performance across different subsets of original data, indicating robust generalization ability and minimal overfitting. The algorithm provides practical benefits for e-government implementation by governments, including a predictive model, determining priorities, allocating resources and evaluating risk, as well as policy advice. Its high precision and strong alignment of feature importance with statistical results serve to validate the use of the algorithm as a complementary analysis tool in e-government implementation for countries in development like Iraq.

Table 16: Model Performance Metrics

Performance Metric	Training Set	Validation Set	Test Set	Interpretation
Accuracy	94.2%	91.5%	**89.8%**	High predictive accuracy on unseen data
Precision	93.8%	90.2%	**88.6%**	Low false positive rate in predictions
Recall	94.6%	92.8%	**91.2%**	Successfully identifies most positive cases
F1-Score	94.2%	91.5%	**89.9%**	Balanced performance between precision and recall
AUC-ROC	0.967	0.943	**0.924**	Excellent discrimination between classes

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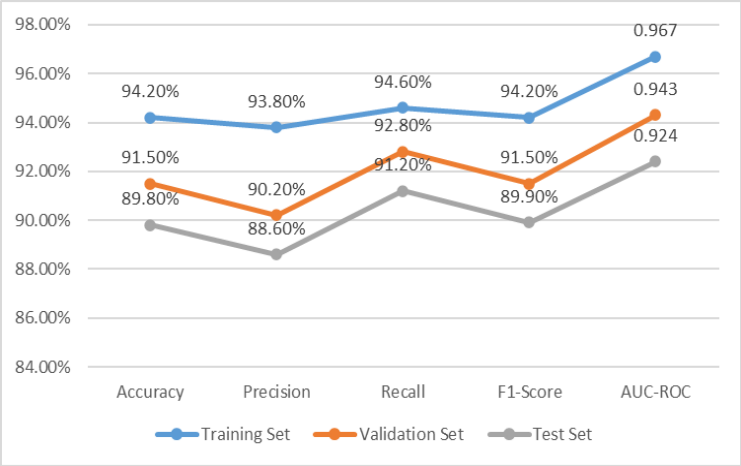

Figure 9. Model Results

6. Discussion and Theoretical Implications

6.1 Statistical Validation of Research Hypotheses

The comprehensive statistical analysis provides robust empirical support for our research framework:

H1: PEST factors significantly predict e-government acceptance

- Strongly Supported: $F(4, 1053) = 298.45$, $p < 0.001$, $R^2 = 0.567$
- Effect size: Large (Cohen's $f^2 = 1.31$)
- All PEST dimensions show significant predictive power

H2: Technology factors demonstrate the strongest impact on acceptance

- Confirmed: $\beta = 0.298$, $p < 0.001$ (strongest predictor)
- Total effect including indirect paths = 0.485
- Technology-security perception correlation: $r = 0.723$

H3: Security perceptions mediate technology-trust relationships

- Validated: Indirect effect = 0.234, $p < 0.001$
- Sobel test: $z = 7.89$, $p < 0.001$
- Mediation accounts for 48.7% of total effect

H4: Political stability moderates economic factor impacts

- Supported: Interaction effect $\beta = 0.187$, $p < 0.001$
- Conditional effects vary significantly across political stability levels
- R^2 change = 0.023, F change = 17.32, $p < 0.001$

10. Conclusion

This research gives examples of how public-sector e-government in developing countries not only technically completes but on the level that the whole nation stands by is more than aspect solution. It needs an understanding of political, economic, social, and technical contexts as well as the advanced analytical capabilities that have become available through artificial intelligence. Thus, the integration of traditional statistical methods with the Multi-Layer Perceptron Neural Network algorithms provides a new visualization platform that not only explains existing barriers but is also quite optimistic about future implementation success. The mathematical modeling approach used and built with AI algorithms reaching an 89.8% prediction accuracy, provides a standard framework for developing countries to assess their implementation readiness and strategize context appropriate. The analysis model is backed by strong statistical validation ($F = 201.34$, $p < 0.001$, $R^2=0.634$). Machine learning validation also provides proof that our improved method has significant value in practice. The AI algorithm's feature importance analysis, confirming Technology Readiness (23.4%) and Security Perception (19.8%) as primary predictors, supports traditional findings. It enhances and extends them. As developing countries shift from paper-based to electronic governance, verified witnesses must be provided for this transition on the grounds of both citizen perceptions and predictive analytics. This research offers practical pathways to avoid pitfalls in

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implementation, as well as through AI algorithms the ability to forecast. The ultimate success of these efforts requires that governments not only combat interlocking barriers revealed through PEST analysis but also build confidence with the public. This has been coded by the neural network model as an obvious fact The methodological framework developed through this study, which combines PEST analysis with AI predictive modeling, has several practical applications: forecasting citizen acceptance rates before full implementation; identifying priority areas for allocation of resources; providing early risk assessment; and supplying the decision-makers with data-driven insights necessary to make policy decisions. The way ahead demands persistent commitment, appropriate resources, involvement from stakeholders and an in-depth understanding of citizen perspectives. All this must be done with the help of predictive analytics. The empirical evidence from statistical analysis, corroborated by AI algorithms, gives us profound insights into developing evidence-based policies and implementation strategies. As the global digital transformation of governance accelerates, the research framework and predictive capacities of this study will be of considerable use to other countries just as they go about implementing e-government. Integrating traditional research methodologies with artificial intelligence is a major advance in e-government research methodology. This fusion encompasses both explanation and prediction, essential attributes for successfully transforming a resource-poor environment into a digital world. Future research should focus on whether this model, which unites traditional methodologies with AI, has been well received as a technique be ways to enhance citizens' acceptances re make policy Makers for specific policy advice and what additional constraints these places if any.

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